

The speed and impact of small vs. ‘big team’ science during urgent societal events

In the first quarter of the 21st century alone, society encountered numerous events that demanded quick, urgent, and widespread action. This includes (a) some of the deadliest terrorist attacks in modern history, (b) a global pandemic, and (c) the sudden public release and uptake of AI technologies. *Urgent societal events*, such as these, represent historically pivotal moments – moments that often signal an impending period of transformative social, political, and/or technological change. Despite the potential significance of science in these moments, a fundamental question remains unresolved: How should the ecosystem of science best organize its response? More specifically, should researchers, funders, and stakeholders prioritize larger, more collectivistic research projects – or smaller, more individualistic efforts?

Previous scholarship on the benefits and drawbacks of large teams in science focuses on how scientists operate in ordinary conditions – not historical moments where society has a sudden, intense, and urgent need for scientific insights. Nonetheless, we used our understanding of the former to reach an informal consensus about expected patterns in the latter: during urgent societal events, larger teams will be more impactful *but slower*.

There are several reasons to expect larger teams to be more impactful in science. Large-scale collaboration (a) allows role specialization¹, (b) increases total effort dedicated to a problem², and (c) creates conditions for facilitating recombinant growth^{3,4}, uncovering the “wisdom of the crowd”^{5,6}, manifesting “collective intelligence”⁷, and leveraging social channels to spread impact⁸. Consistent with this reasoning, bibliometric investigations suggest that larger teams receive more citations across a variety of domains, including: scholarly articles^{8–12}, patents⁹, code repositories⁹, news outputs¹³, and policy documents¹³. This impact, however, is often suggested to come at a cost that may be particularly noteworthy during urgent societal events: speed. More specifically, it takes time to assemble a large team⁷, negotiate responsibilities⁵, navigate different institutional policies⁶, coordinate the actual work¹⁴, track contributions⁸, and manage disagreements⁸. Working with a small team may be quicker, with more streamlined coordination, fewer bureaucratic constraints, and greater decision-making agility.

To more formally evaluate scientists’ performance during urgent societal events, we formed an *adversarial collaboration*: a procedure in which scholars with diverging perspectives work together to accelerate progress on an outstanding scientific issue^{15–17}. Collectively, our collaboration involves researchers who have historically advocated for (a) relatively *big* teams in science², (b) relatively *small* teams in science⁹, and (c) more neutrally, team science efforts designed to bridge differing perspectives on complex issues¹⁸. Connecting bibliometric databases containing over 250 million scientific publications, 2.6 billion citations in scholarly works, 25 million mentions in news outlets, and 25 million mentions in public policy documents, we examine the success of scientific responses to urgent societal events in terms of the speed and impact of publications.

Our initial investigation yielded surprising results: big teams were not only more impactful, but also *quicker* to publish their insights. This investigation involved research articles containing keywords linked to three events: (1) the 2001 World Trade Center attacks, (2) the COVID-19 pandemic, and (3) the initial release of the generative AI tool, ChatGPT. To examine the speed of scientists’ published responses, we identified the approximate dates when each urgent societal event entered mainstream public awareness: September 2001 (World Trade Center attack), March 2020 (World Health Organisation’s declaration of COVID-19 pandemic), and November 2022 (public release of ChatGPT). Response speed was measured as the number of days between the onset of each event and the publication date of each article mentioning

associated keywords (“terrorism”, “COVID-19”, and “ChatGPT,” respectively). In addition to their speed, we examined the impact of these articles. Here, we measured the cumulative number of citations received from other scholarly articles, news media, and policy documents.

Using weighted linear mixed-effect regression, results indicated that each additional co-author on a published research response was associated with a (a) 0.19 percentile increase in scholarly citations (95% CI [0.19, 0.19], $t(1382544) = 180.55$, $p < .001$), (b) 0.30 percentile increase in news citations (95% CI [0.30, 0.30], $t(539112) = 135.89$, $p < .001$), (c) 0.16 percentile increase in public policy document citations (95% CI [0.16, 0.16], $t(539033) = 89.45$, $p < .001$), and (d) .006 percentile decrease in days to publish (95% CI [-0.006, -0.006], $t(478544) = -6.91$, $p < .001$). Expressed in raw units, each additional co-author was associated with 1.08 more scholarly citations, 0.38 more news citations, 0.02 more policy citations, and a .07 day (2 hour) delay in publication speed.

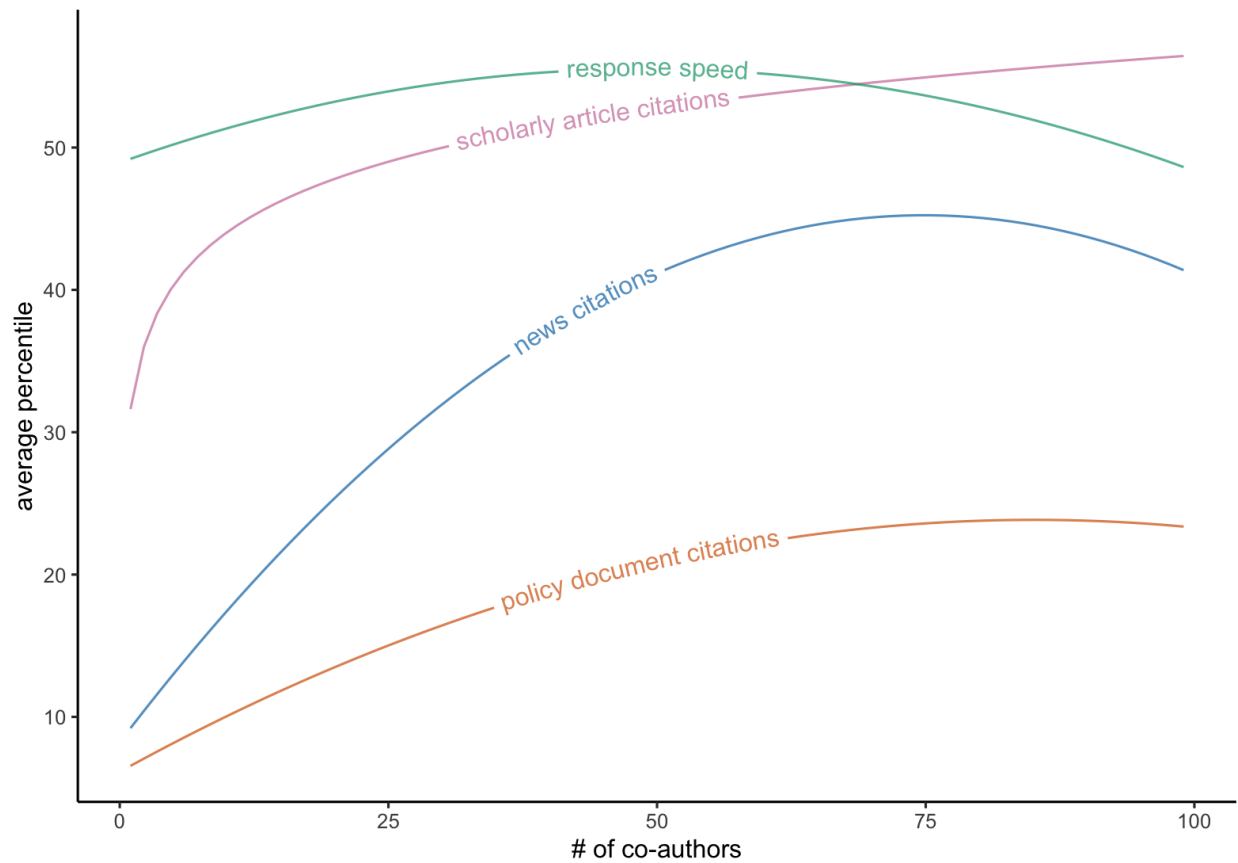
Of course, linear regression assumes that increases in team sizes are associated with *constant* (linear) rates of returns in speed and impact. However, it is unlikely that such relationships are actually linear. For instance, increases in team size may yield *diminishing* returns in terms of impact¹⁹ – building towards a plateau where scientists must make increasingly larger investments to increase the speed and impact of their work. Alternatively, this relationship may be more *curvilinear*: increases in team size may lead to improved performance up to a point, after which further growth becomes *detrimental*. Such possibilities were evaluated via logarithmic and quadratic regression, respectively.

In our analyses, the relationship between team size and scholarly citations was best captured by a logarithmic model, indicating diminishing returns. This model showed substantial improvement over both the linear ($\Delta\text{BIC} = 23,985$) and quadratic models ($\Delta\text{BIC} = 5,073$), with $\beta_1 = 7.94$ (95% CI [7.94, 7.94], $t(1382401) = 239.49$, $p < .001$). For all other outcomes, quadratic models achieved best fit. For news citations, the quadratic model improved over linear ($\Delta\text{BIC} = 5,466$) and logarithmic models ($\Delta\text{BIC} = 772$), with $\beta_1 = 0.99$ (95% CI [0.99, 0.99], $t(538959) = 104.11$, $p < .001$) and $\beta_2 = -0.01$ (95% CI [-0.01, -0.01], $t(539076) = -74.33$, $p < .001$). The quadratic model also best fit policy citation data (linear $\Delta\text{BIC} = 1,101$; logarithmic $\Delta\text{BIC} = 530$), with $\beta_1 = 0.42$ (95% CI [0.42, 0.42], $t(539029) = 53.59$, $p < .001$) and $\beta_2 = -0.002$ (95% CI [-0.002, -0.002], $t(1382542) = -81.72$, $p < .001$). Similar patterns were also found for speed (linear $\Delta\text{BIC} = 6,652$; logarithmic $\Delta\text{BIC} = 6,081$), with $\beta_1 = 0.27$ (95% CI [0.27, 0.27], $t(691381) = 77.59$, $p < .001$) and $\beta_2 = -0.003$ (95% CI [-0.003, -0.003], $t(1382542) = -81.72$, $p < .001$). These quadratic effects suggest that while larger teams initially benefit impact and speed, performance often declines beyond a threshold. These estimated points of decline were 75 co-authors for news citations ($z = 13.33$), 85 for policy citations ($z = 15.28$), and 49 for speed ($z = 8.42$). Such sizes lie far outside typical team norms, indicating that the limits of collaboration are rarely exceeded (see Figure 1)¹³.

These results – if reliable – have implications for both theory and practice. Theoretically, they help uncover the functional dynamics of a socially unique response to urgent societal events: mass collaboration^{20–22}. Practically, such findings may also inform evidence-based scientific responses to *future* urgent societal events – such as an intensified “AI race”^{23,24}, a potential H5N1 avian influenza virus outbreak²⁵, or efforts to radically shift political, economic, and social systems²⁶. Indeed, if building up big teams (at least up to a certain size) produces faster and more impactful papers, the scientific enterprise would have to undergo substantial transformation to better align norms, incentives, funding models, and infrastructure to support larger teams^{2,27,28}.

Next steps: We are prepared to submit a full-length manuscript within the next month. However, we have identified data from 45 additional urgent events that could be used for a Registered Report.

Figure 1. Modeled relationships between the number of paper co-authors (x-axis) and four outcomes: response speed (green), mentions in scholarly articles (pink), news media (blue), and policy documents (orange). Analyses are based on 1,382,547 papers published within the three years of the September 11 terrorism attacks, COVID-19 pandemic, and the release of ChatGPT.



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